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Technology heterogeneity in European industries' energy efficiency performance. The role of climate, greenhouse gases, path depedence and energy mix.

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Abstract

Assessment of industrial-level energy efficiency development is a critical research topic that has infiltrated in the global battle against climate change. A balanced panel of fourteen European industries from twenty-four countries for the period 1995-2011 is introduced into a metafrontier framework. Reflecting the divergent views on the importance of desirable and undesirable outcomes in the pursuit of energy efficiency, the proposed approach estimate industrial performance by prioritizing either economic or environmental criterion incorporating technological heterogeneity. It is found that small-scale economies exhibit persistent high energy efficiency scores. Regarding energy efficiency determinants, path dependence phenomena have a strong presence, climate characteristics occurs, while energy mix displays linear but also non-linear relationships. Finally, regardless of the method employed, there is a strong evidence of conditional and unconditional convergence.

Keywords: European industries, Energy efficiency, Technology heterogeneity, Directional distance function, Energy mix, Path dependence, Convergence.

1 Introduction and motivation

Industrial activities in Europe are in the foreground of the policy agenda imposing a heavy burden on the quality of the environment. Under this perspective, European industries have perceived the huge potential benefits from adopting energy saving and environmental friendly technologies aiming at a lower impact on the environment. A clean and energy saving manufacturing sector has been targeted as a key area for Europe particularly since the European Directive 2009/28-33 (European Council, 2009). Thus, building up an energy efficient European industry can benefit European countries by improving their welfare, with greater levels of energy independence and security, achieving the underlying objective of cost minimization and facing successfully the threat of energy rising prices. Additionally, it can evolve into a valuable asset for reducing CO_2 emissions, fulfilling Kyoto protocol, enhancing industry competitiveness and promoting economic growth through continual innovation. The efforts made by European Commission at this direction result a rather questionable outcome concerning energy efficiency (European Commission, 2011), highlighting the strategic role of improved energy efficiency.

The Paris Agreement (2015) as well as the Climate Action Conference (2018) in Seoul and Katowice Summit (2018), where the importance of a threshold in global temperature was emphasized, are the most recent paradigms of the importance of environmental policies on energy and emissions. With this frame of mind, EU continues its commitment to reduce greenhouse gas emissions, be energy efficient and use energy from renewable sources by 20% in 2020 compared to 1990 levels. In continuance of the Kyoto Protocol (1997), the first international agreement on climate change, and Copenhagen Summit (2009) EU has set a new list of targets to be achieved by the end of 2030 and 2050 in order to become a low-carbon economy. More precisely, the Directives "Energy end-use efficiency and energy services" of 2006 (2006/32/EU) and "Energy efficiency directive" of 2012 (2012/27/EU; EED) try to implement several policies for industries, such as financial, informational, legislative, fiscal measures and market-based instrument (EU Emissions Trading). Their main target group are small-medium firms by diffusing accessible information on energy matters and large companies by making audits for energy consumption. However, because of the economic and financial crisis (2008-2012) that struck Europe, the results for energy efficient industries and countries were not the expected ones revealing heterogeneous patterns.

The last few decades, the concept of energy efficiency has drawn a lot of attention from policymakers to managers and researchers. However, because of its nature, it is difficult to be calculated. The first researchers assessed it using the IDA analysis that had taken under consideration the economic, structural and energy changes of an economy. As time has gone by, the notion of energy intensity became identical with the measure of energy efficiency. Nonetheless, this measure serves as a partial energy efficiency due to the absence of non-energy inputs in its estimation. This argument specifies the necessity for a new universal integrated approach.

The aim of this paper is to fill this gap in the literature by providing new evidence on energy efficiency measures and the factors that affect it using a European industrial sample. Moreover, this research aims at enlightening the role of technology heterogeneity and country hierarchies in the benchmarking process revealing specific idiosyncrasies. The adopted methodology operates in two stages, allowing us to reveal possible differences for energy efficiency measures under a country and a European technology framework. Furthermore, through this lens we provide a concrete evaluation as whether possible group of variables are likely to increase energy efficiency with respect to the different technologies. We deploy a fully nonparametric approach to perform benchmarking on energy efficiency scores across industries in the sample using data envelopment analysis and directional distance function approaches. We then complement this with a second stage analysis using Tobit regression models to establish how industrial energy efficient performance has been affected by a variety of industry and country specific variables. Finally, we proceed with a convergence analysis for our energy efficiency measures.

The obtained results show that countries with small-scale economies are unexpectedly energy efficient. Moreover, when undesirable outputs are included in our analysis, scores change dramatically for the majority of industries. On the other hand, the non inclusion of technological heterogeneity that incurs in Europe and the consideration that industries compete each other solely on the boundaries of a national level, lead easily to overestimated energy efficiency scores. In this case, several industries which were efficient in their country, become inefficient when they are compared with others outside of their economy. This indicates that many factors, mainly the path dependence, the climate and the energy mix that uses each industry, initiate linear or nonlinear relationships with turning points with energy efficiency.

The paper is structured as follows: The next Section reports the literature review, highlighting open issues, while Section 3 develops the methodological approach adopted in this study. Section 4 presents the data including a description of energy and CO_2 emissions across European countries. In Section 5 the results and discussion are given, while

Section 6 concludes and suggests for future research in the final section.

2 Review of the literature

Energy efficiency is a multifaceted concept with a vital role for industries' energy strategy. From the seminal paper of Berndt and Wood (1975), who engaged with the notion of energy and its substitution elasticity relation with capital and labor, to Patterson's (1996) energy efficiency different divisions[1], several authors tried to measure energy efficiency using different methodologies. The first attempts to measure energy efficiency were focused on the decomposition of energy consumption, through a bottom up framework, using Index Decomposition Analysis (IDA)[2] and on energy intensity, defined as the amount of energy used per unit of output-activity. However, IDA measures have a number of shortcomings which have become increasingly evident, as more sophisticated parametric and non-parametric models are brought to bear on distributional questions (Shorrocks, 2013). On the other hand, energy intensity seems to not take into consideration non-energy inputs that exist in the production process, which establishes it as "partial" energy efficiency.

Bearing the above-mentioned shortcomings some authors have paid attention on the production theory framework (i.e Filippini and Hunt, 2012). The basic idea is based on the estimation (using parametric or nonparametric approaches[3]) of a best practice frontier for the use of energy. Thus, energy efficiency can easily be computed as the difference of the actual and the predicted energy use introducing the total factor energy efficiency index (TFEE) (Hu and Wang, 2006). In the literature, relating to Stochastic Frontier Analysis, the derivation of the Shepard distance function allows for the estimation of shadow prices (Zhou et al., 2012; Lin and Du, 2013), the curvature of the sustainability along the frontier (Färe et al., 2005) and the derivation of "underlying energy efficiency" (Filippini and Hunt, 2012).

Comparing the two approaches we can argue that the majority of the relevant studies on energy efficiency follows the parametric approach aiming on TFEE calculation. A significant number of empirical studies following the nonparametric approach is mainly concentrated on China

[1] Mainly into thermodynamics index, physics–thermodynamics index, economy–thermodynamics index and pure economic index.

[2] Indicatively see Ang and Zhang, 2000; Fisher-Vanden et al., 2004 for further discussion.

[3] The nonparametric approach is known as Data Envelopment Analysis (DEA) while the parametric as Stochastic frontier Analysis (SFA).

(Wei et al., 2012; Wang et al., 2014) and India (Paul and Bhattacharya, 2004; Worrell et al., 2009), either by focusing on provinces, or on an industrial and firm level. On the other hand, the last few decades, the concept of energy efficiency has amused progressively researchers to conduct similar studies in OECD and in APEC Countries and in Europe on a minor extent (Hu and Kao, 2007; Zhou et al., 2008; Voigt et al., 2014). Notwithstanding, a divergence of various methods is occurred when the measure of energy efficiency is computed. Some scholars follow Hu and Wang (2006) seminal definition of energy efficiency (Zhou et al., 2008; Grösche, 2009) while, a small part adopts slack based measures (i.e Li et al., 2012).

The major weakness of Hu and Wang (2006) definition concerning the inclusion of undesirable output constitutes a common aspect of the aforementioned studies. The undesirable outputs, such as CO_2 emissions, are generated because of the increment of fossil fuel energy use (Ramanathan, 2006). Thus, the necessity of a joint production of both desirable and undesirable outputs in the measurement of energy efficiency indeed exists (Wu et al., 2005; Zhou and Ang, 2008; Mandal, 2010). In this direction, Färe et al. (1996) utilized distance functions to incorporate bad outputs and environmental regulations into the efficiency analysis. The directional distance function (DDF) expands good and contracts bad outputs and inputs according to the direction vector that is adopted (Chambers et al., 1998). Therefore, the presence of CO_2 emissions in the production process as well as the environmental regulations can induce distinct estimations of energy efficiency (Picazo-Tadeo et al., 2005; Watanabe and Tanaka, 2007). On the contrary, several studies have outspread the conventional DDF to the non-radial DDF by embodying slacks and they argued that the reduction of undesirable outputs and the increase of desirable outputs should not be fluctuated at the same rate (Färe and Grosskopf, 2010; Wang et al., 2013; Apergis et al., 2015), while others employ its parametric concept which is mostly used for assessing the shadow prices of pollutants (Färe et al., 2005; Vardanyan and Noh, 2006).

A common feature of previous studies is that they refer to the same restraint of heterogeneity in their production technology. The ignorance of technological heterogeneity that encompasses differences in economic development, industrial structure, resource endowment and geographical environment can easily lead to biased estimations (Battese et al., 2004) leading to the isolation hypothesis (Tsekouras et al., 2016). However, a small number of studies have utilized the metafrontier approach within the DEA method (Sala-Garrido et al., 2011; Wang et al., 2013), SFA (O'Donnell et al., 2008), Malmquist index (Fei and Lin, 2016), parametric approach (Lin and Du, 2013) and DDF (Zhang et al., 2013; Yao et al., 2015; Li and Lin, 2015).

In all these papers, energy efficiency has been calculated using distance function under an input-output mix. Although good progress towards understanding energy efficiency estimation issues has been made, only few studies have been conducted for the examination of the factors that affect it. The majority of them use the decomposition analysis to indicate the factors that determine energy intensity, which consists a partial energy efficiency index (Ma and Stern, 2008; Metcalf, 2008). However, it is still vague which factors can actually affect the measure of energy efficiency. As Abadie et al. (2012) argued, it can be influenced by structural, undesirable, climatic and energy factors, while Cui et al. (2014) added that a tax exemption amount of high-technology energy companies, as a management indicator, can benefit energy efficiency. On an industrial level, these determinants can be classified more precisely into technological, sectoral and country's specific characteristics (Shao et al., 2011; Pan et al., 2013). Finally, Stavins et al. (2010) detected that the industrial structure optimization is the main factor that can provoke energy reduction and consequently an increase in energy efficiency.

3 Methodological Underpinnings and Hypotheses Tested

Our methodological framework is developed in two interconnected stages. In the first stage, we present the theoretical and methodological underpinnings regarding the estimation of the directional distance function. At the same time, we discuss expansion in a metafrontier framework presenting the theoretical basis for its inclusion. Finally, in the second stage we discuss our econometric approach.

3.1 A Data Envelopment Analysis and a Directional Distance Function approach

To formalize these concepts, we briefly introduce a notation. Consider i industries at K countries which employ a vector of inputs $x \epsilon \mathbb{R}^n_+$ to produce a vector of desirable output $y \epsilon \mathbb{R}^m_+$. The production possibility set (Banker et al., 1984) at any given period t can be represented by the closed set: $T = \{(x, y) : \text{x can produce y}\} \epsilon \mathbb{R}^{n+m}_+$ while the input set defined as: $L(y) = \{x \epsilon \mathbb{R}^n_+ : (x, y) \epsilon T\}$. The input-oriented efficiency regarding T can be measured with reference to the input set through the direct input distance function: $D_I(x, y) = sup\{\theta > 0 : \frac{x}{\theta} \epsilon L(y)\}$.

Thus the productive efficiency for the i-th industry (x,y) in each of the examined European country is defined as in Eq. 1.

$$\hat{E}ff_{i/c}(x,y) = min\{\theta|\theta > 0, y_i \leq \sum_{i=1}^{n} \gamma_i y_i; \theta_x \geq \sum_{i=1}^{n} \gamma_i x_i\} \qquad (1)$$

for γ_i such that $\sum_{i=1}^{n} \gamma_i = 1, \gamma_i \geq 0, i = 1, 2, ..., n$
The input oriented DEA implementation allows for the calculation of energy efficiency. Following closely Hu and Wang (2006), energy efficiency of an industry i that belongs to a country K at time t can be calculated using the following formula:

$$TFEE_{i,t|K} = \frac{Target\ Energy\ Input_{i,t|K}}{Actual\ Energy\ Input_{i,t|K}} = \frac{Actual\ Energy\ Input_{i,t|K} - Total\ Adjustments_{i,t|K}}{Actual\ Energy\ Input_{i,t|K}}$$

or

$$TFEE_{i,t|K} = 1 - \frac{Radial\ Adjustment_{i,t|K} + Energy\ Input\ Slack_{i,t|K}}{Actual\ Energy\ Input_{i,t|K}} \qquad (2)$$

where i=1, 2, ..., I refers to each DMU - industry, t=1, 2, ..., T refers to time period and K=1, 2, ..., K refers to each country.

The amount of total adjustments, which includes the total amount of inputs that should be conformed by an industry so as to reach its optimal production efficiency, can be determined as the summation of radial and slack adjustments that an industry achieves. The index of TFEE lies between zero and unity, whilst the greater the value of TFEE, the more efficient the energy is consumed (Hu and Wang, 2006; Honma and Hu, 2008; Zhang et al., 2011).
In the case where CO_2 emissions have been included in the production process, we employ a vector of $x \epsilon \mathbb{R}^n_+$ to produce a vector of $y \epsilon \mathbb{R}^m_+$ desirable output and a vector of $b \epsilon \mathbb{R}^q_+$ undesirable output. Now, the production set in which a unit can produce good and bad outputs using x inputs, is defined as: $T^b = \{(x, y, b)$: x can produce (y,b)$\} \epsilon \mathbb{R}^{n+m+q}_+$.

The directional distance function[4] allows for the simultaneous existence of good and bad outputs in the production framework (Chambers et al., 1998; Färe and Grosskopf, 2004; Färe et al., 2005). The technology set T^b adhere to a series of axioms, as Shepard (1953, 1970) argued. These axioms include that: The technology set is closed, convex and bounded (Chambers et al., 1998), inactivity is allowed, "free lunch" is not allowed (Kumar, 2006), good outputs are exposed to strong disposability, good and bad outputs share a "null-jointness" and undesirable outputs are involved with weak disposability when environmental regulations exist. The directional distance function is defined as:

[4] See in the supplementary material for a more analytic description of LP program.

$$\overrightarrow{D}_T(x,y,b;d) = sup\{\delta : (y+\delta d^y, b-\delta d^b)\epsilon P(x-\delta d^x)\} \quad (3)$$

where $d = (-d^x, d^y, -d^b)$ is a vector of directions which seeks for the maximum possible expansion of desirable outputs in the d^y direction and the maximum feasible contraction of inputs and undesirable outputs in the directions d^x and d^b respectively. Because of the fact that we wanted to presume upon that an industry aims on an increment in the production of good outputs and a reduction in bad outputs/inputs simultaneously, we employed the direction vector d=(-1,1,-1). It is worth mentioning that TFEE follows the same logic as before, for its calculation in the DDF approach.

3.2 DEA and DDF under a Metafrontier Framework

In the previous section, each industry owns a distinguishing case of technology T or T^b and its own environmental aspects that fit to a specific country. However, subtracting the assumption of technological isolation between countries (Tsekouras et al., 2017) and including the notion of heterogeneity (Battese et al., 2004), the introduction of metafrontier analysis is fundamental for our study. The reason is that the technology of a group (country) can not include characteristics such as resource endowments, economic infrastructure, other characteristics of the physical, social and economic environment (O'Donnell et al., 2008; Kounetas, 2015) and national, legal and institutional regulations (Halkos and Tzeremes, 2011; Kontolaimou and Tsekouras, 2010). The advantage of the metafrontier framework is that each industry can now be compared with industries around Europe as all of them experience the same frontier. Therefore, an industry that was efficient with respect to its country frontier, could be inefficient when the European metafrontier comes into play.

Therefore, the meta frontier technology for each one of the two methods can be considered as the convex hull of the jointure of individual technologies:

$$T^M_{DEA,DDF} = conv\{T_1UT_2UT_3U...UT_K\}$$

$$T^M_{DEA} = \{(x,y)x,y > 0 : \text{x can produce y in at least one of } T_1, T_2, ..., T_C\}$$

$$T^M_{DDF} = \{(x,y,b)x,y,b > 0 : \text{x can produce y,b in at least one of } T_1, T_2, ..., T_C\}$$

As O 'Donnell et al. (2008) pointed out, a meta technology ratio (MTR) which measures the distance between the group frontier and the meta frontier for a DMU i with reference to DEA is defined as:

$$MTR^{DEA}_{i|K} = \frac{MEE_{i|K}}{EE_{i|K}} = \frac{\theta^{MF}_{DEA}}{\theta^{F}_{DEA}}$$

In the case of DDF method, according to Chiu et al. (2012), the measure is ginen as:

$$MTR_{i|K}^{DDF} = \frac{MEE_{i|K}}{EE_{i|K}} = \frac{1-\beta_{DDF}^{MF}}{1-\beta_{DDF}^{F}}$$

where θ^{MF} and θ^{F} are the energy's efficiency score for DEA, whilst β^{MF} and β^{F} are the energy's inefficiency score of DDF method on metafrontier and frontier respectively.
As MTR reaches unity, the distance between group and metafrontier is being diminished, while when it is equal to unity, the group and the metafrontier technology are identical.

3.3 The determinants of energy efficiency

In the second stage of analysis, in order to avoid specification errors as it does not exist any formal theory about the determinants of energy efficiency, we combined elements as specified in the literature, by controlling for climate indicators, economy structure in conjunction to a set of technological characteristics at an industrial level, intensities and the energy mix.

Given the bounded range of the dependent variable (varying from zero to one), following the literature, we employ a panel Tobit model (i.e Wang et al., 2013; Li and Shi, 2014; Watanabe and Tanaka, 2007) with robust standard errors to explore the main research question of this paper. The choice of the particular methodological route is justified by the fact that the outcome variable is censored. We specify and estimate the following empirical models for the case of the metafrontier and that of the countries' frontier:

$$EE_{i,t|F,MF}^{DEA,DDF} = \alpha + BEE_{i,t-1|F,MF}^{DEA,DDF} + \mathit{\Gamma} EnMix_{i,t|F,MF}^{j} + \mathit{\Delta} EnMix_{j,i,t|F,MF}^{2}$$
$$+ZClimZone_{i,t|F,MF}^{l} + HIntensities_{i,t|F,MF}^{m} + \mathit{\Theta} ProdChar_{i,t|F,MF}^{p} + \varepsilon_{i,t|F,MF} \quad (4)$$

where variable $EE_{i,t}$ is referred to the calculated measure of energy efficiency for each industry i at time t. $EnMix_{i,t}^{j}$ expresses the energy mix shares and the exponent j=(1,...,5) each time is referred to petroleum, gas, electricity, solid fuels and renewable energy shares respectively.[5] $EnMix_{i,t}^{2}$ consists the quadratic term of energy mix shares for each industry i at time t. Squares are usually utilized so as to assimilate trend effects into the analysis (Abadie et al., 2012). Therefore, in order to capture any decreasing or increasing marginal effects that may exist among energy mix shares and energy efficiency as time goes by, the utility of the quadratic term was deliberate. According to Köppen Climate

[5]The energy share of nuclear energy was omitted.

Classification, we separated the European countries in 5 different climate zones where l=(Cfb,[6]Csa,[7] Csb,[8]Dfb,[9]Dfc[10]). The variable $Intensities^{m}_{i,t}$, where m=(1,2), is constituted by Energy and CO_2 Intensity for each industry i at time t while $ProdChar^{p}_{i,t}$, where p=(1,..,4), is composed of 3 productive fractions.[11] Lagged values have also been included to downsize autocorrelation and alleviate endogeneity concerns. The parameters $B, \Gamma, \Delta, Z, H, \Theta$ are to be estimated while the disturbance term $\varepsilon_{i,t}$ captures the unobserved factors affecting energy efficiency levels.

4 Data and variables

In order to facilitate our study we employ a unique dataset that allows us to (i) examine production and energy efficiency performance under weak and strong disposability (ii) introduce some apparent meaningful associate heterogeneity (iii) examine possible energy efficiency factors and (iv) test for the convergence hypothesis on our energy efficiency measures. The employed dataset has been created by combining information by four distinct available sources. European industries consists the decision making units under examination. So, data on 2-digit fourteen manufacturing industries according to the International Standard Industrial Classification (ISIC) from 27 European countries[12] are comprised over a seventeen-year period, from 1995 to 2011 for the two parts of our analysis. Thus, our dataset contains 6426 observations in the panel dimension.

The first part of our dataset which is utilized in the non-parametric estimation of the production frontier, using both DEA and DDF method, involves two outputs and four inputs. We approximate the produced output (Y), by the gross valued added of each industry in million Euros. Moreover, the undesirable output, in our case CO_2 emissions, is linked with energy combustion and expressed in metric tons.[13] The input set

[6]Oceanic climate: Belgium, France, Germany, Ireland, Luxembourg, Netherlands, Spain, United Kingdom.

[7]Hot-summer Mediterranean climate: Cyprus, Greece, Italy, Malta.

[8]Warm-summer Mediterranean climate: Portugal.

[9]Humid continental climate: Austria, Bulgaria, Czech Republic, Denmark, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia, Sweden.

[10]Subarctic climate: Finland.

[11]Capital/Labour, Capital/Energy, Labour/Energy and the percentage of Manufacturing sector in each economy at time t.

[12]See Appendix A Table 1.

[13]We are fully aware that CO_2 emissions are presented in line with UNFCCC accounting rules and IPCC reporting guidelines, which do not often readily capture changes in fuel and the sectoral mix of energy use both upstream, (Kounetas, 2018).

consists of the capital stock[14] (K) in million Euros, the labor input (L) which is captured by the total hours worked by employees, expenditure on intermediate inputs (M) in million Euros and the total energy consumption (E) measured in million tons (Mtoe) of oil equivalent. Regarding energy consumption we used total primary energy supply (TPES) in units of tons of oil equivalent per thousand year-2000 purchasing price parity (PPP) million Euros. All the monetary variables have been deflated and are expressed in Euros in constant 1995 prices. The upper part of Table 2 illustrates the descriptive statistics of the input-output variables.

A closer inspection of the input-output variables in Table 3 reveals some interesting features. For instance, the growth rates between energy consumption and emissions have a separate affiliation, as 10 countries out of 27 share a positive growth on both variables, 5 out of 27 share a negative parallel path, while 12 out of 27 have a counterbalancing growth relation. This sustains the fact that among countries exists a significant level of heterogeneity that could easily lead to biased estimations on industrial energy efficiency. Moreover, the high value of standard deviation, especially in terms of the intermediate inputs and CO_2 emissions, strengthens the picture of a non homogeneous sample. Therefore, a deeper analysis in the manufacturing sector of European countries is necessary in order to distinguish the influencing factors that might provoke those fluctuations and affect energy efficiency measures. This search of factors could benefit institutions for the implementation of environmental policies aiming on energy maintenance and emission reduction.

These factors could be classified into four discrete categories. The first group concentrates on environmental aspects and their relations with the output performance of each industry (Ma and Stern, 2008; Kounetas, 2018). Such factors are energy and CO_2 intensity that point out the cost of "transposing" energy and CO_2 emissions into GDP.

The second group is referred to factors that are more energy - concentrated (Li and Shi, 2014; Schmidt et al., 2017; Abadie et al., 2012). Energy consumption can be divided into five wider categories: renewable (RS), electricity (ES), petroleum (PS), gas (GS) and solid fuels (SFS) shares (Stern, 2012). This separation helps us to understand the role, magnitude and direction of each energy activity on energy efficiency, as each industry and country use different quantities of energy mix in production. Focusing on European policies surrounding energy and climate change, each European country is required to comply with the EU

[14]The PIM method has been applied: $K_{i,t} = (1-\delta)K_{i,t-1} + I_{i,t}$,where δ is equal to 10%, as it is the most used rate in capital calculation.

guideline in order to tackle pollutants-waste, switch from non-renewable sources to renewable ones and eventually to supervene energy efficiency and security.

Meanwhile, the industrial economy of European countries continues changing in its internal infrastructure. Economic and social development are connected with their success. Industries attempt to change their technological perspectives, be energy "friendly" and adapt to socio-economic shocks to become more profitable and diminish their costs. For this purpose, we employ as the third category of factors, proxies for capital, human and energy costs (the capital-labor, capital-energy and labor-energy structure) (Stavins et al., 2010; Tsekouras et al., 2017) and the proportion of manufacturing sector in each market economy, reflecting the productive characteristics of industries.

The last group of factors that may affect energy efficiency of industries is related to climate dimension. European countries do not share the same climate which initiates variations in the energy consumption of industries, and, as a result, distinct outcomes in industrial energy efficiency. Consequently, we generated dummy variables for each one of the five climate zones (according to Köppen Classification) in order to incorporate the climate effects that exist around Europe.

For the whole set of industries, all data are provided from definite, specific databases. Data for Gross Value Added, Labor, Intermediate Inputs and CO_2 emissions were collected through the World Input Output Database (WIOD),[15] while data concerning capital from Organization for economic co-operation and development (OECD)[16] and energy consumption from Enerdata Odyssey.[17] For the econometric part of the analysis, data for the energy mix were drawn from Eurostat[18].

5 Results and discussion

The presentation and discussion of the empirical results follow the two stage structure of the analysis. The industry-specific energy efficiency scores with respect to the country frontiers are first presented and discussed. The metatechnology energy efficiency scores which arise in the context of the metafrontier have been presented. Finally, the econemetrics reulsts of energy efficiency determinants are discussed.

[15]http://www.wiod.org/home

[16]https://data.oecd.org/

[17]https://www.enerdata.net/solutions/database-odyssee.html

[18]https://ec.europa.eu/eurostat

5.1 European industries' energy efficiency

The efforts made by European countries and their industries in following Kyoto protocol obligations and European Directives provide contradictory results concerning energy consumption reduction, emissions abatement and renewables diffusion (Jacobsson and Johnson, 2000; Energy Commission, 2011[19]; Morris et al., 2012; Trianni et al., 2013; EIA, 2017[20]). In this regard, a clear insight and detailed picture of European industrial energy efficiency performance is more than appropriate for governments and organizations, regulators, scholars, policy makers and economists. At this point, it is crucial to note that all efficiency measures are grounded on a cross-section basis estimated separately for each year in the sample.[21]

Table 4 summarizes the main results with respect to the country specific frontier and the metafrontier respectively. On the whole, average energy efficiency scores for their frontier (country) case, are highly efficient irrespectively the method employed. In particular, countries like Cyprus, Malta, Austria, Czech Republic, France, Italy, The Netherlands, Poland, Portugal, Slovakia, Slovenia and Spain appear to be among the most energy efficient ones, attaining average scores more that 90% using the two approaches. Turning our attention to the metatechnology, we estimate energy efficiency scores under the condition that all industries have access to a common technology known as the European metatechnology. Again, Malta and Cyprus show relatively high energy efficiency measures, contrary to the other countries, but at a significant lower rate. Countries that hold big scarcities of resources might develop a straighter and more considerable policy and management of the production leading to better efficiency scores than countries that live in prosperity and try to maximize the output without having to worry much about the ideal combination of resources. Moreover, it is obvious that energy efficiency averages are quite low compared with the previous ones. In advance, the distributions on energy efficiency with respect to the metatechnology are presented using a kernel density in Figure 1. A bimodal behavior exists for both approaches but with completely different tails.

The relaxation of the technological isolation assumption (Tsekouras et al., 2016) allows to study the impact of pure technical spillover effects generated at the European level, affecting individual industrial energy efficiency performance that co-exist at the European technology level.

[19] `https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2011:0885:FIN:EN:PDF`

[20] `https://www.eia.gov/outlooks/ieo/pdf/0484(2017).pdf`

[21] The estimations of energy efficiency measures have been carried out employing R program.

Thus, we can assume that all European industries share the possibility of technological interaction with each other. However, the extent of knowledge assimilation and performance enhancement heavily relies on the absorptive capacity and appropriability conditions (Nelson and Winter, 1982) of each national economy. Moreover, it seems that, at a significant degree, industries can't exploit the technological opportunities, especially in the energy sector (Breschi et al., 2000) and use efficiently the external sources of opportunities (Reichstein and Salter, 2006) revealing non significant incoming spillover effects (Tsekouras et al., 2016).

In addition, the time evolution of the energy efficiency scores with respect to the metatechnology, depicted in Figure 2, reflects a process of continuous and quite significant downward trend for the majority of the countries participated in our sample. However, some countries, such as Cyprus and Malta, have a divergent path as their process tend to be balanced and permanent around the maximum efficient level.

Apart from the findings concerning energy efficiency with reference to the individual technology and metatechnology at a country level, it is interesting to consider the results concerning the examined industries with respect to the metafrontier. Table 5 presents the energy efficiency scores under the metafrontier case. When referring to this case, we can denote that on average terms, energy efficiency of manufacturing industries of Electrical and Optical Equipment, Leather and Footwear, and both Machinery and Equipment n.e.c. and Transport Equipment, at a lower rate, perform better in contrast to the rest of the sample. As someone could argue, in the manufacturing industry the competition is of higher intensity between entities, which pushes the demand for energy on greater levels than the usual ones and the implementation of cost-effective energy efficiency measures is of paramount importance. However, the results reflect that the most energy efficient industries are those who are considered as non - energy intensive industries. Therefore, the use of less energy consumption of the last ones could be a crucial factor for the level of both energy efficiency and the amount of CO_2 emissions.

Nonetheless, in the same manner, it is crucial to examine the industries that, diachronically, perform best on the metafrontier. As such, we can mention the industry of Leather and Footwear as the leader and the one who adopts a new technology when it is available. The fact that the particular industry is situated in both technical[22] and energy efficiency scores this high, can be justified by the fact that those two efficiencies could supposedly have a strong connection. When an industry is tech-

[22]See supplementary material (Table 2).

nical efficient, it means that, in input orientation, it can minimize its inputs as much as possible, given that its outputs will remain at the same level. Therefore, the particular industry owns the best technology level and production process in order its inputs and outputs to perform at the optimal level. Next, is the Chemicals and Chemical Products in DEA method and Other Non-Metallic Mineral Products in DDF. The rest of the industries that have not reached the frontier yet, can follow those industries as examples and adjust their technology and production process in order to boost their efficiency.

Finally, the time evolution of European industries for the metafrontier case is depicted at Fig. 3. In general, it indicates that industries own a descending trend as time goes by. The only exception seems to be Coke, Refined Petroleum Products which follows a converse path in one of the two methods displayed. The industries of Transport Equipment, Manufacturing and Recycling, Machinery Equipment, Electrical and Optical Equipment, Rubber and Plastic Products and Leather and Footwear tend to adhere to the same comportment as their efficiency levels on average are equal to one until 2003 and from this point until the end of the time period they present a decline on their efficiency.

At the end, through the application of the Wilcoxon and Kruskal-Wallis test, for the sake of the differentiations that exist among industries, we reject the null hypothesis, at a significance level of 1%, that the existence of CO_2 emissions in the production function has no modifications on the levels of energy efficiency.[23]

5.2 Econometric results for energy efficiency determinants

One important player on improving energy efficiency is the industrial sector which is responsible for about 35 of the total energy use in Europe (Eurostat, 2018). However, it is still obscure, in a theory matter, which are those variables that affect energy efficiency on the industrial level and in which direction their impact will be. In the same manner, it is crucial to understand which are the main determinants of energy efficiency performance and to estimate, in advance, their impact. The influencing factors of energy efficiency, as indicated in the second stage of our analysis, are shown in Table 6. The existence of two types of technology frontiers, under both DEA and DDF method, has contributed to the differences that are observed between variables.

To this direction, one should account for path dependence phenomena (David 2001) of energy efficiency i.e to what extent energy efficiency

[23]For more details, see supplementary material (Tables 6 and 7).

performance of previous periods has an impact on the current. This first core factor has a positive and significant effect for both DEA and DDF approaches, indicating that the greater the value of energy efficiency the previous year, the better for the current one (Cowan and Hulten, 1996; Unruh and Carrillo-Hermosilla, 2006). Thus, European industries perform better in terms of energy, both with respect to the industry frontier and the metafrontier, when they acquire the proper elements of the diffusion of energy knowledge and technology (Fouquet, 2016), signifying the importance of past accumulated knowledge and technical capabilities. The higher energy efficiency levels from the previous year will ensure a smaller extent of energy use in the present which highlights the fact that path dependence is "a probabilistic and contingent process" where future paths or technologies are based upon the current and past states of the system at hand (Martin and Sunley, 2006). Moreover, the specific finding for the European industries case, irrespectively the methodology employed, signifies the role and the impact of past decisions, states, choices on energy efficiency not only on the current but also on the future path (Page, 2006). The latter is in accordance with Comin and Hobijn (2010) finding of significant "technology locking". Under a dynamic perspective, path dependence could be easily extended to specific energy system technological trajectories that lead to technological, full or partial, "lock-in" (Fouquet, 2016). This robust and long-lived energy "lock-in" can be explained by the presence of infrastructural (Bleakley and Lin, 2012), technological, institutional and behavioral (Stuetzer et al., 2016) individual lock-ins (Fouquet, 2016).

As Berndt and Wood (1975) and Hudson and Jorgenson (1974) proposed, the substitution between energy input and the rest of inputs in the production function is real and their relationship should be studied more thoroughly. Therefore, the use of productive characteristics such as the ratios between inputs are necessary as explanatory variables of energy efficiency (second group of factors). It is worth mentioning that the capital over labor ratio affects, both in frontier and metafrontier, positively energy efficiency which could induce a shrinking on the gap that exists between industries from different countries. On the other hand, labor over energy affects negatively energy efficiency while capital over energy acts in accordance with the capital over labor ratio. The productive structure of the economy consists a significant factor of energy efficiency. The estimated results point out that the most significant ratio for industries is that of capital to labor. Additionally, the contribution of manufacturing sector to national output plays a significant positive role on the economic growth of a country and consequently on the energy efficiency of industries.

In the majority of studies (i.e Cui et al., 2014; Li and Shi, 2014), energy consumption is the foremost and most important factor of energy efficiency and their relationship is positive. However, when energy consumption "breaks" into categories (i.e coal, electricity, renewable) it does not follow a certain path and presents fluctuations. In order to evaluate in more depth this relationship, we proceeded with the investigation of different energy types on energy efficiency. Our key results show that, at the whole, EU industries' energy efficiency has been significantly affected by the energy mix. The specific results hold for the majority of the energy types irrespectively of the energy efficiency's estimation approach employed. Thus, differences in the energy primary mix play a rather important role among EU industries. However, we have to recall that the energy type omitted was nuclear, meaning that the estimated coefficients for the other energy sources are in reference to that source. Moreover, in this research, we examine each category of energy consumption on its own and we additionally insert into our econometric analysis the quadratic terms to examine the existence of a non-linear relationship and if the effect of each category is diminishing or increasing on energy efficiency (U-type or inverse U-type shape).

According to our results, oil and coal appear to have a non-linear relationship for the metafrontier and the frontier case, indicating a strong inverted U-shape. This relationship is documented for both DEA and DDF approaches. This denotes a "paradoxically" increase of energy efficiency as oil and coal consumption increases when it meets a turning point where energy efficiency decreases as oil and coal continues to increase. The same holds for gas, but only for the metafrontier case. These results are seemingly surprising as a pure negative effect was expected (Stern, 2012). Various points stand out in this regard. Firstly, the most positive linear effect is associated with oil consumption while gas and coal follow with slight difference denoting completely different slopes.

Two possible explanations arise at this point. The first one is related to energy stacking hypothesis and energy ladder phenomenon (i.e Hosier and Dowd, 1987; Masera et al., 2000). Thus, while the necessity for new, cleaner fuels is more than obvious, the adoption of climate friendly technologies and fuels serve as a particular partial, rather than perfect substitutes, for coal and oil for the EU industries. The specific results reveal the fact that energy transition does not occur in a discrete, linear and serial transition from one technology into another, but in a rather more complex way. In advance, it explains more clearly the relationship between energy efficiency and energy mix denoting the role of severe turning points and the existence of U-shaped or inverted U-shaped relationships. Finally, it returns to our debate the significant evidence of technology locking (Comin and Hobijn, 2010) justifying the fact that it takes longer time for new technologies (i.e renewable) to dominate the market.

The second explanation arises from two different aspects of energy sources; energy quality and the cost of the fuel (i.e Cleveland et al., 2000; Brown and Ulgiati, 2004). The examination of those two aspects is important because some energy fuels can produce more comparing with others (Stern, 2010; Liddle, 2012) while their costs of use may vary significantly (Liddle, 2012). Under this perspective, oil and coal, as one of the most efficient in terms of energy performance and the least expensive compared with electricity, can be the most preferable one. Moreover, it is not irrelevant that in the energy economics literature, it is well known that several studies also relate the energy stacking phenomenon with energy fuel characteristics and the choice of the most "desired and best" fuel available (Smith et al., 1994; Van der Kroon et al., 2013).

We continue by exploring, at this stage, the effect of electricity and renewable fuels on energy efficiency. Considering the estimation results with respect to the metafrontier, improvements in electricity and renewable consumption have a significant effect on energy efficiency. Our results reveal a U-shaped relationship between energy efficiency and consumption specific levels. In particular, as consumption increases, energy efficiency initially decreases and then increases as consumption continues to raise. In advance, when CO_2 emissions are concerned in production, gas and electricity show a significant linear positive and negative impact on energy efficiency respectively. This suggests that promoting the use of clean energy in the manufacturing process can reduce emissions and ameliorate energy efficiency's levels.

Turning next to the case of intensities, we employ CO_2 emissions and energy intensity as proxy variables capturing energy changes (Stavins et al., 2010). With respect to the metatechnology case, CO_2 intensity appears with a negative and statistical significant effect on energy efficiency for both approaches. However, the picture is completely different for the individual country frontiers since the negative sign is not significant. It is straightforward that technical knowledge, technological capabilities and absorptive capacity arising in the context of incoming spillovers (Tsekouras et al., 2016), seem to play a crucial role in determining GHGs behavior of European industries. In contrast, the sources of production technology heterogeneity pose significant difficulties weakening emissions' intensity effect. Thus, resource endowment, different stages of economic development, market conditions and geographical position shape different production processes that make the effect of the specific variable to be non significant. In the case of energy intensity, it is found to be statistical significant solely for the metatechnology and the DDF approach. When we employed energy intensity, we expected a positive relationship between EE and EI (partial energy efficiency), as Zhou and Ang (2008) underlined. The specific results arguably supports that energy intensity indicator may be viewed as a rough proxy of energy efficiency for the European industries case.

Finally, the variety that exists on climate among European countries has lead to discrepancies on the outcome and the magnitude of each climate zone on energy efficiency. It is obvious that the weight of each climate zone is different and consistent with our expectations, both in DEA and DDF method. This points out that countries such as Poland, Sweden and Finland that are located closer to North Pole exhibit lower temperatures and precipitation rates over the year. Such being the case, industries that belong to these countries will need larger amounts of energy in order to be efficient and be compared with the rest of Europe.

5.3 Convergence analysis of energy efficiency

In the current section we proceed with β and σ convergence tests to examine if there is a negative correlation between the initial level of energy efficiency and its growth rate and to investigate changes in the cross-sectional variance of energy efficiency over time. Following Solow (1956), from the neoclassical stochastic growth model, to Quah (1996) and Sala-i-Martin (1996), we estimate the β-convergence in order to investigate the convergence of energy efficiency. Equation 5 shows the regression for β-convergence of the energy efficiency:

$$EE_{jt}^{F,MF} - EE_{j0}^{F,MF} = \alpha + \beta EE_{j0}^{F,MF} + \epsilon_{jt} \tag{5}$$

where $\mathrm{EE}_{jt}^{F,MF}$ is the logarithm of energy efficiency for industry j in time t for each case, $\mathrm{EE}_{j0}^{F,MF}$ is the value in the initial period,α and β are the parameters and ϵ_{jt} is the error term. The "half life" is calculated through the ratio $\frac{log2}{\beta_j}$. Nevertheless, on the grounds of the vast criticism of β convergence (i.e Quah, 1996), we further adopt σ convergence that measures the change in the value of the standard deviation over time (t=0, ..., T). Carree and Klomp (1997) provided the extent of the statistical significance of the σ convergence assuming no σ convergence for the sample industries ($i = 1, \ldots, n$) (null hypothesis) using the following formula:

$$\sigma_{it} = \sqrt{N}\frac{\frac{\hat{\sigma}_{i0}^{2}}{(\hat{\sigma}_{it}^{2}-1)}}{2\sqrt{1-(1-\hat{\beta}_{it})}} \tag{6}$$

The estimated results of the β regression are presented in Table 7. The β-convergence coefficients for both frontier and metafrontier approaches are negative and statistically significant at the significance level of 1%, except for the case of DEA with respect to metafrontier. This points out that industries with lower initial level of energy efficiency could acquire higher growth, and converge to the best practice frontier, than industries with higher initial levels of efficiency. Finally, Table 8 reports the standard deviation and the coefficient of the two series for energy efficiency. To formally test the null hypothesis of equal variances the table also reports the t-test proposed by Carree and Klomp (1997). As it can be seen, there is a statistically significant variance decrease. In other words, we came across with unequivocal evidence in favor of both unconditional β and σ-convergence for our variable of interest.

6 Conclusions

Increasing efforts are necessary to encourage for even more renewable energy, greater energy efficiency and innovation for energy saving technologies, since the world's advanced economies performed a rise in their carbon dioxide emissions in 2018, bucking a five year-long decline (IEA, 2018). The specific finding justifies the role of energy efficiency and saving implementation strategies to European industries as an ongoing and hotly contested subject matter, still in need of thorough empirical and theoretical investigation. Existing literature investigates energy efficiency as a simple estimation measure for different entities. Moreover, the examination of possible factors that affect energy efficiency remains inconclusive.

This study contributes new evidence by employing an empirical framework that allows us to introduce and examine energy efficiency, possible determinants and convergence issues, which have to this point remained largely unexplored within the energy economics literature. By adopting the latest approaches on industrial operational performance evaluation, we investigate whether industrial energy efficiency is committed to path dependence phenomena, climate characteristics and specific intensities and if it has been affected by their energy mix. In advance, we examine the above-mentioned research questions taking into account the role of technology heterogeneity and possible industrial idiosyncrasies and specificities that emanate from country specific technological, economic, social, institutional and infrastructure differentials. Finally, we search for possible energy efficiency convergence paths during the period of examination.

Our findings, based on the analysis of a unique sample of 14 European industries from 27 European countries over the period 1995-2011, provide distinct paths for energy efficiency. First of all, as far as countries are concerned, almost half of them demonstrate more than 90% energy efficiency scores. Furthermore, when undesirable outputs are included in the analysis, energy efficiency scores change dramatically for the majority of industries. Moreover,the non inclusion of the technological heterogeneity that incurs in European countries and the consideration that industries compete each other solely on the boundaries of a national level lead easily to overestimated energy efficiency scores. In the metafrontier case, the majority of industries present a downward trend through time which suggests that,on average, European industrial energy efficiency declines.

We establish the robustness of our main conclusions by further concentrating on industry characteristics and measures relating to energy efficiency. In doing so, we obtain an even richer picture concerning patterns of nonlinearity in energy structure effects to industrial energy efficiency performance. More specifically, our results reveals inverted U-shaped relationships for oil and coal fuels denoting the role of energy stacking and quality. Moreover, the reported effects for renewable and electricity fuels suggest a U-shape relationship. Our results confirm that path dependence phenomena have a strong presence on energy efficiency, irrespectively of the methodology approach adopted, indicating the role of past accumulated knowledge, technical capabilities and technological "lock-in". It is evident that different climatic characteristics play a crucial role on energy efficiency revealing a negative impact for all of our cases. According to convergence analysis, it also appears that industries with lower initial levels of energy efficiency could converge to the best practice frontier easier.

However, limitations such as the lack of a concrete and solid theoretical framework about the determinants of energy efficiency, data on environmental expenditures and taxes of each industry and energy prices, for the whole set of our sample, and the quantitative form of environmental regulations for European countries were large obstacles for this study. Nonetheless, we believe that this paper could be a reliable tool for policy makers, governments and firms to understand the notion of energy efficiency and the techniques to improve it. Further analysis of this study could be the enlargement of the dataset, by combining more years and countries as well as the consideration of more undesirable outputs in the production function.

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Appendix A

Table 1: List of European Countries and Manufacturing industries

Country (Code)		Code	Industry name
Austria (AUT)	Latvia (LVA)	BMF	Basic Metals and Fabricated Metal Products
Belgium (BEL)	Lithuania (LTU)	CHM	Chemicals and Chemical Products
Bulgaria (BGR)	Luxembourg (LUX)	CRP	Coke, Refined Petroleum Products
Cyprus (CYP)	Malta (MLT)	ELO	Electrical and Optical Equipment
Czech Republic (CZE)	Netherlands (NLD)	FBT	Food, Beverages and Tobacco
Denmark (DNK)	Poland (POL)	LEF	Leather and Footwear
Estonia (EST)	Portugal (PRT)	MAC	Machinery and Equipment n.e.c.
Finland (FIN)	Romania (ROU)	MAN	Manufacturing and Recycling
France (FRA)	Slovakia (SVK)	ONM	Other Non-Metallic Mineral Products
Germany (DEU)	Slovenia (SVN)	PPP	Pulp Paper, Paper, Printing and Publishing
Greece (GRC)	Spain (ESP)	RUP	Rubber and Plastic Products
Hungary (HUN)	Sweden (SWE)	TXT	Textiles and Textile Products
Ireland (IRL)	United Kingdom (GBR)	TRE	Transport Equipment
Italy (ITA)		WCP	Wood and Wood and Cork Products

Note: The European Classification of Industries was based on NACE division (NACE Rev. 2 Section C)

Table 2: Summary Statistics of inputs and outputs of European Manufacturing Sector (1995-2011)

		Mean[a]	Std. Dev.	Min	Max
	Outputs				
	Y	4052.21	9211.25	0.06	125754.30
	CO_2	2819.41	6871.76	0.02	67864.28
	Inputs				
	K	702.70	1482.66	0.02	15465.37
	II	9206.96	20361.30	0.03	255747.40
	L	167.21	267.06	2.13	2025.01
	E	3.34	13.12	0.01	149.87
	Explanatory variables				
	SFS	0.06	0.07	0.01	0.61
	PS	0.41	0.16	0.13	0.81
Energy mix	GS	0.43	0.96	0.01	6.00
	RS	0.03	0.04	0.01	0.19
	ES	0.18	0.05	0.08	0.36
Intensities	EI	0.50	0.59	0.01	5.00
	$C0_2I$	0.22	0.01	0.01	2.00
Productive	K/L	1	1.00	0.01	25.79
characteristics	Ms	17.75	5.08	5.21	30.23
	Cfb	0 = 70.37%			
		1 =29.63%			
	Csa	0 =85.19%			
		1 =14.81%			
Climatic	Csb	0 = 96.30%			
characteristics		1 = 3.70%			
	Dfb	0 =51.85%			
		1 =48.15%			
	Dfc	0 =96.30%			
		1 =3.70%			

[a] Frequencies are reported for dummy variables

Table 3: Mean growth rates of inputs and outputs variables

	Mean values of 1995 - 2011						Growth (%)					
	Y	II	K	L	CO2	E	Y	II	K	L	CO2	E
AUT	2759,52	5160,36	433,37	79,35	1812,78	1,50	67,66	206,05	19,29	-0,17	21,27	0,01
BEL	3116,63	8248,70	508,89	69,29	3206,80	3,95	36,92	127,28	-0,64	-1,07	-35,49	0,03
BGR	16,83	52,07	3,55	83,91	1119,46	0,94	-9,19	-25,75	-1,39	-1,46	-67,93	-0,03
CYP	54,84	109,22	9,69	5,82	131,15	0,07	0,00	1,36	0,33	-0,06	2,11	0,01
CZE	1236,53	4338,42	373,32	192,42	1890,69	1,65	86,73	353,89	22,09	-0,05	-17,05	-0,01
DNK	1525,55	3136,10	373,31	47,22	575,34	0,84	-1,07	46,97	16,85	-0,97	-6,17	-0,01
EST	69,27	205,55	19,86	17,94	139,06	0,11	3,14	8,65	1,12	-0,45	1,78	0,01
FIN	2626,80	4645,10	286,59	50,23	1300,17	1,96	126,93	159,49	2,38	-0,10	2,03	0,02
FRA	14742,46	43436,25	2088,31	383,19	9094,36	10,47	296,48	2122,25	28,99	-8,10	-99,99	0,03
DEU	30690,69	61046,87	4346,68	814,44	13504,04	16,70	616,60	1825,68	65,32	-10,46	-177,09	0,02
GRC	798,37	1834,64	124,20	81,71	1109,17	1,81	7,41	-3,60	1,80	0,57	6,20	0,02
HUN	590,31	2197,63	162,43	134,27	832,01	1,06	18,98	102,45	7,52	-0,12	-13,00	0,01
IRL	1892,31	4005,10	267,76	39,62	567,75	0,45	82,97	214,68	18,52	-0,02	10,26	0,01
ITA	13641,86	36969,91	3803,39	618,15	10471,15	11,37	-76,35	280,38	63,28	-5,13	-34,50	0,01
LVA	50,24	76,52	15,23	19,24	110,70	0,06	1,31	1,21	0,30	-0,79	-2,98	0,01
LTU	600,64	1135,20	173,77	33,56	338,97	0,66	31,09	47,75	11,25	-0,82	7,33	0,02
LUX	162,63	376,87	34,13	5,33	177,63	0,08	2,57	10,03	1,02	-0,05	-7,44	0,01
MLT	42,26	107,78	9,16	8,27	8,06	0,00	-0,07	-1,48	-0,16	-0,15	0,66	0,01
NLD	4131,02	9558,17	654,58	109,58	3265,34	7,74	103,93	179,94	8,73	-0,90	-25,03	0,01
POL	2105,55	5999,73	414,14	381,61	5468,57	3,76	101,67	427,88	12,03	-2,61	-178,87	0,01
PRT	1167,32	3157,82	306,36	122,48	1412,40	1,57	10,02	23,32	10,89	-2,79	9,34	0,01
ROU	64,51	161,48	16,23	273,11	1459,59	1,94	-3,55	-6,63	-0,42	-4,98	-63,63	-0,03
SVK	601,27	1896,29	138,32	64,95	1542,54	0,95	35,75	126,95	6,76	-0,89	-13,34	0,01
SVL	234,99	515,87	62,38	31,07	211,91	0,13	4,75	8,89	3,34	-0,72	-1,57	0,01
ESP	6845,17	18226,89	1505,60	337,33	7237,76	7,30	56,86	368,02	42,10	-1,91	119,95	0,05
SWE	5165,73	7138,69	701,02	91,97	1256,93	2,67	317,55	200,30	12,18	-0,92	-7,11	0,01
GBR	14476,59	24850,68	2140,74	418,81	7879,79	10,49	82,04	-12,74	48,84	-9,44	-152,41	-0,05

Table 4: Countries' Efficiency results

	DEA		DDF			DEA		DDF	
Country	FEE	MFEE	FEE	MFEE	Country	FEE	MFEE	FEE	MFEE
AUT	0.919	0.379	0.953	0.605	LVA	0.846	0.313	0.942	0.576
	(0.170)	(0.328)	(0.149)	(0.,395)		(0.299)	(0.303)	(0.188)	(0.402)
BEL	0.760	0.310	0.942	0.629	LTU	0.847	0.392	0.950	0.722
	(0.331)	(0.270)	(0.183)	(0.383)		(0.280)	(0.256)	(0.151)	(0.350)
BGR	0.825	0.129	0.943	0.700	LUX	0.879	0.598	0.960	0.791
	(0.281)	(0.230)	(0.169)	(0.373)		(0.253)	(0.330)	(0.122)	(0.342)
CYP	0.933	0.659	0.967	0.864	MLT	0.932	0.740	0.940	0.883
	(0.188)	(0.346)	(0.136)	(0.287)		(0.168)	(0.299)	(0.149)	(0.269)
CZE	0.912	0.090	0.975	0.363	NLD	0.940	0.319	0.999	0.596
	(0.214)	(0.092)	(0.092)	(0.322)		(0.196)	(0.299)	(0.009)	(0.396)
DNK	0.845	0.371	0.951	0.706	POL	0.936	0.113	0.984	0.461
	(0.243)	(0.298)	(0.137)	(0.360)		(0.165)	(0.155)	(0.079)	(0.382)
EE	0.893	0.195	0.930	0.562	PRT	0.977	0.190	0.991	0.517
	(0.260)	(0.187)	(0.220)	(0.394)		(0.083)	(0.190)	(0.067)	(0.398)
FIN	0.586	0.286	0.756	0.545	ROU	0.857	0.030	0.944	0.460
	(0.423)	(0.255)	(0.368)	(0.400)		(0.279)	(0.050)	(0.200)	(0.405)
FRA	0.920	0.328	0.967	0.582	SVK	0.939	0.170	0.985	0.608
	(0.197)	(0.324)	(0.126)	(0.380)		(0.188)	(0.150)	(0.104)	(0.381)
DEU	0.775	0.378	0.883	0.658	SVL	0.944	0.214	0.983	0.485
	(0.327)	(0.393)	(0.247)	(0.363)		(0.114)	(0.188)	(0.087)	(0.392)
GRC	0.814	0.239	0.933	0.438	ESP	0.934	0.230	0.976	0.528
	(0.260)	(0.240)	(0.167)	(0.390)		(0.163)	(0.259)	(0.100)	(0.408)
HUN	0.851	0.137	0.917	0.456	SWE	0.470	0.348	0.636	0.566
	(0.297)	(0.135)	(0.214)	(0.390)		(0.413)	(0.313)	(0.417)	(0.390)
IRL	0.706	0.429	0.932	0.727	GBR	0.784	0.286	0.953	0.537
	(0.347)	(0.342)	(0.196)	(0.370)		(0.303)	(0.346)	(0.115)	(0.382)
ITA	0.993	0.238	1.000	0.627	Total	0.852	0.300	0.937	0.600
	(0.028)	(0.253)	(0.001)	(0.373)		(0.280)	(0.312)	(0.193)	(0.394)

Note: Standard deviation in parentheses

Table 5: Industries' Energy Efficiency results with respect to the Metafrontier

Scores of Energy Efficiency					
Industry	DEA	DDF	Industry	DEA	DDF
BMF	0.171	0.513	ONM	0.168	0.796
	(0.243)	(0.404)		(0.234)	(0.304)
CHM	0.270	0.474	PPP	0.272	0.457
	(0.334)	(0.404)		(0.278)	(0.394)
CRP	0.264	0.669	RUP	0.330	0.607
	(0.366)	(0.412)		(0.281)	(0.400)
ELO	0.416	0.777	TXT	0.283	0.466
	(0.333)	(0.303)		(0.295)	(0.392)
FBT	0.198	0.483	TRE	0.350	0.771
	(0.199)	(0.390)		(0.307)	(0.311)
LEF	0.501	0.669	WCP	0.270	0.471
	(0.364)	(0.380)		(0.285)	(0.407)
MAC	0.379	0.663	Total	0.300	0.600
	(0.327)	(0.347)		(0.312)	(0.394)
MAN	0.333	0.580			
	(0.296)	(0.381)			

Note: Standard deviation in parentheses

Table 6: Marginal effects after panel Tobit model

		Metafrontier		Frontier	
		DEA	DDF	DEA	DDF
Path Dependence	EE_{t-1}	0.198***	0.401***	0.525***	0.616***
		(0.005)	(0.010)	(0.012)	(0.013)
Energy mix	PS	0.467***	0.452***	0.265***	0.163***
		(0.087)	(0.115)	(0.086)	(0.056)
	GS	0.032***	0.028**	0.015	0.004
		(0.008)	(0.012)	(0.009)	(0.006)
	RS	-0.049***	-0.041***	-0.006	-0.001
		(0.009)	(0.013)	(0.010)	(0.006)
	ES	-0.395***	-0.420***	0.080	0.170**
		(0.102)	(0.148)	(0.109)	(0.073)
	SFS	0.028***	0.051***	0.019**	0.012**
		(0.007)	(0.011)	(0.008)	(0.005)
	PS^2	-0.158***	-0.155***	-0.140***	-0.086***
		(0.040)	(0.055)	(0.042)	(0.027)
	GS^2	-0.009*	-0.010	0.001	0.003
		(0.005)	(0.007)	(0.005)	(0.003)
	RS^2	0.033***	0.025***	0.002	-0.001
		(0.004)	(0.006)	(0.005)	(0.003)
	ES^2	0.113**	0.118	-0.119**	-0.135***
		(0.051)	(0.075)	(0.056)	(0.038)
	SFS^2	-0.003*	-0.008***	-0.006***	-0.004***
		(0.001)	(0.002)	(0.002)	(0.001)
Intensities	EI	0.006	0.016**	0.006	0.001
		(0.005)	(0.007)	(0.005)	(0.003)
	$C0_2I$	-0.017***	-0.024***	-0.009	-0.001
		(0.005)	(0.007)	(0.006)	(0.003)
Productive characteristics	K/L	0.004***	0.013***	0.003*	0.002**
		(0.001)	(0.002)	(0.001)	(0.001)
	K/E	0.002**	0.005***	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
	L/E	-0.001*	-0.001**	-0.001	-0.001
		(0.005)	(0.001)	(0.001)	(0.001)
	Ms	0.057***	0.106***	0.018	-0.001
		(0.015)	(0.023)	(0.015)	(0.009)
Climatic characteristics	Cfb	-0.037***	-0.023**	-0.019**	-0.013***
		(0.007)	(0.010)	(0.008)	(0.004)
	Csa	-0.019***	-0.009*	-0.017***	-0.009***
		(0.003)	(0.005)	(0.004)	(0.002)
	Csb	-0.005***	-0.002*	-0.005***	-0.002***
		(0.001)	(0.001)	(0.001)	(0.001)
	Dfb	-0.059***	-0.037**	-0.035***	-0.020***
		(0.010)	(0.014)	(0.012)	(0.007)
	Obs	6048	6048	6048	6048
	Log (pseudo)likelihood	1140.108	-169.501	1829.960	3750.395
	Model parameters				
	Sigma u	0.086***	0.183***	0.368***	0.466***
		(0.005)	(0.014)	(0.022)	(0.039)
	Sigma e	0.173***	0.341***	0.325***	0.429***
		(0.001)	(0.004)	(0.005)	(0.012)
	Intra-class coefficient (ρ=0)	0.197	0.223	0.562	0.540
		(0.022)	(0.027)	(0.030)	(0.042)

Note 1:Climate zone Dfc is omitted because of collinearity
Note 2:Standard errors in parentheses
Note 3: ***, ** and * denote that variables are statistically significant at the 1%, 5%, 10% levels respectively
Note 4: All models include constants

Table 7: Estimated results for β - convergence

Explanatory	Frontier		Metafrontier	
Variable	DEA	DDF	DEA	DDF
α	-0.510***	-0.233***	-2.336***	-1.599***
β	-0.813***	-0.661***	0.085	-0.306***
Weighted Statistics				
R^2	0.142	0.040	0.005	0.023
Half-life	6.610	10.240	NA	30.342

Table 8: Estimation Results for σ - convergence

Explanatory	Standard deviation		Variation coefficient		T3 test	
Variable	1995	2011	1995	2011	t-statistic	Prob.
Frontier						
DEA	0.215	0.274	-3.678	-3.914	17.185	0.000
DDF	0.244	0.310	-4.059	-4.294	17.856	0.000
Metarontier						
DEA	0.264	0.295	-4.411	-4.516	-18.145	0.000
DDF	0.347	0.354	-4.576	-4.854	-19.354	0.000

Appendix B

Figure 1: Distribution of Energy Efficiency with respect to the Metafrontier

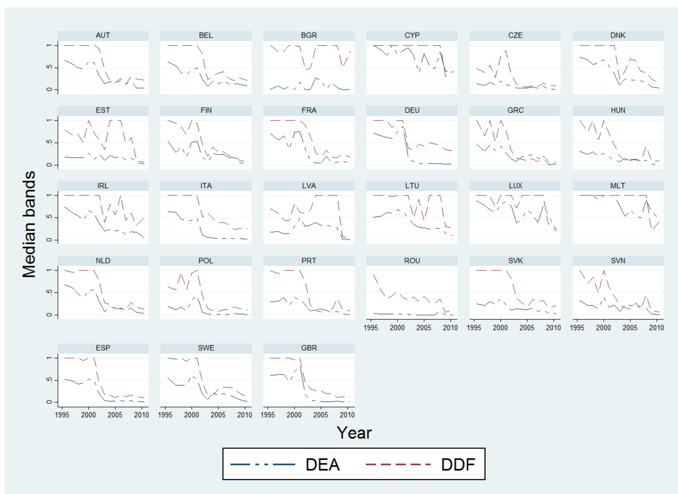

Figure 2: Energy efficiency tendency of European Countries in 1995-2011 with respect to the Metafrontier

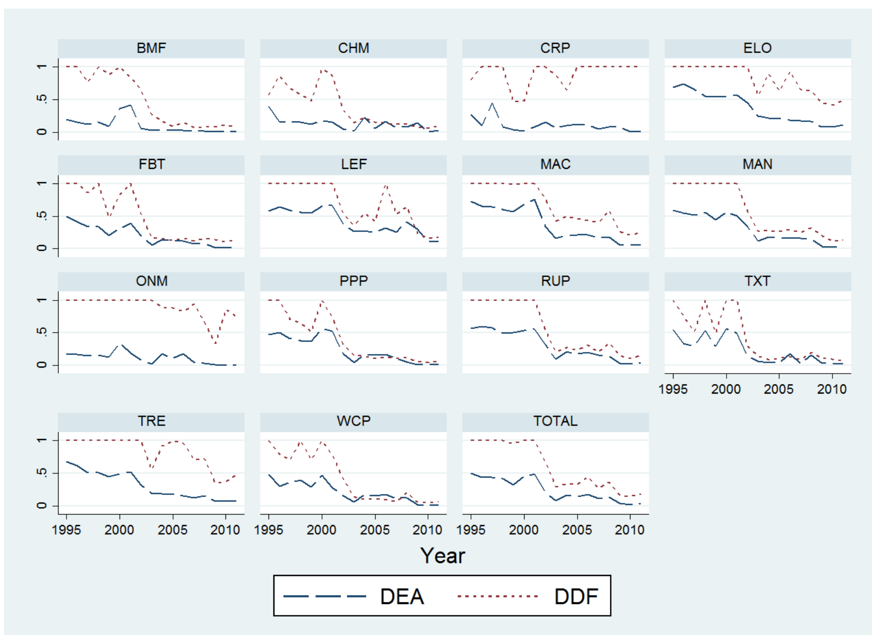

Figure 3: Energy efficiency tendency of European Industries in 1995-2011 with respect to the Metafrontier

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